Automated Fault Diagnosis Using Maximal Overlap Discret Wavelet Packet Transform and Principal Components Analysis

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Abstract

Bearings and gears are components most susceptible to failure in electromechanical systems, especially rotating machines. Therefore, fault detection becomes a crucial step, as well as fault diagnosis. Over decades, substantial progress in this field has been observed and numerous methods are now proposed for feature extraction from monitoring data. Among these data, vibration signals are most used. However, in the presence of non-Gaussian noise, most conventional methods may be inefficient. In this paper, a hybrid methodology is proposed to address this potential issue. The proposed methodology uses a combination of the Maximal Overlap Discrete Wavelet Packet Transform (MODWPT) and Principal Component Analysis (PCA) techniques. First, the MODWPT technique decomposes the vibration signal with uniform frequency bandwidth, facilitating effective signal processing and introducing diversity for enhanced time-frequency signals. Then, to identify significant patterns and characteristics related to faults, PCA is used for 3D dimensional representation of system health state by capturing the variance in the extracted features. Subsequently, a self-organizing map (SOM) is used for system state classification for diagnostics. This technique is applied to open-access test bench data containing vibration signals with non-Gaussian noise.

Keywords: Signal processing, Fault diagnosis, Gearbox, Feature extraction, Rotating machines, MODWPT.

1. Introduction

Bearings and gears have significant roles in both traditional and modern manufacturing processes due to their extensive applicability (A. Soualhi et al., 2014; Benaggoune et al., 2020). As technology progresses rapidly, bearings and gears are often used in industrial equipment and systems (Gougam et al., 2021). Consequently, any bearing or gear failure can have a profound impact on the entire production process, resulting in economic losses and potentially fatal accidents. Consequently, early bearing and gear failure diagnosis becomes a critical step in preventing premature and catastrophic failures throughout the manufacturing process. Detecting and addressing gear failures is fundamental in preventing serious economic losses and potential accidents. A robust failure detection and isolation technique is required to monitor the rotational components and identify any damage (Abdeltwab & Ghazaly, 2022). Currently, many researchers are focusing on monitoring conditions using vibration signals. Various conventional methods, such as the Fast Fourier Transform, the Wigner Ville distribution (Dhok et al., 2020), short-time Fourier transform (S. Zhou et al., 2020), and cyclo-stationary analysis (Gilles, 2013; Adel et al., 2022; Patel & Upadhyay, 2020), have been employed. However, background noise often obscures defect-characteristic information, resulting in non-stationary, non-linear behavior of the data signal. Hence, such methods are regarded as ineffective in extracting features indicating early defects. Several adaptive decomposition methods have been introduced in recent decades for feature extraction. As a promising example, empirical mode decomposition (EMD), proposed by Huang, has been widely explored and applied to mechanical fault diagnosis (Meng et al., 2022). EMD decomposes a discrete-time signal into individual components called intrinsic mode functions (IMFs). Each IMF includes an oscillating component with several frequency levels, and the determination of the sifting iteration number is determined by a sifting stop criterion (SSC) (Fan et al., 2020). In the decomposition process, EMD uses a specialized filter with a bandwidth and center frequency that adjust dynamically according to the signal's characteristics.

Nevertheless, HHT presents two major drawbacks derived from EMD: mode mixing, in which waves of the same frequency are assigned to different intrinsic mode functions (IMFs), and end effects, which lead to incorrect instantaneous values at both ends of the signal (Afia, Gougam, Rahmoune, et al., 2023). A more appropriate decomposition method needs to be considered. Consequently, wavelet analysis has returned to the center of attention, in particular the discrete wavelet transform (DWT), widely used in condition monitoring and fault diagnosis to extract time-frequency features (Syed & Muralidharan, 2022). Unfortunately, DWT requires the sample size to be precisely 2 (down-sampling) during the analysis (Wang et al., 2021). An enhanced version of the discrete wavelet transform, known as the Maximal Overlap Discrete Wavelet Transform (MODWT), handles the sampling reduction process, yet still remains plagued by inadequate frequency resolution, similar to that of the discrete wavelet transform [14]. To address such limitations, the Maximal Overlap Discrete Wavelet Packet Transform (MODWPT) has replaced both MODWT and DWT, providing improved resolution. MODWPT decomposes the complex signal into single components of instantaneous amplitude and frequency, ensuring circular shift equivariance to monitor the gear's working condition (Afia et al., 2024a). For automated health monitoring, various machine learning techniques are used to provide more accurate predictions (M. Soualhi et al., 2021; Lourari et al., 2024; Benaggoune et al., 2022; M. Soualhi et al., 2019; Gougam, Afia, Aitchikh, et al., 2024; M. Soualhi et al., 2020; Afia, Gougam, Touzout, et al., 2023; Tahi et al., 2020; Touzout et al., 2020; A. Soualhi et al., 2012; Gougam, Afia, Soualhi, et al., 2024; Afia et al., 2024b). The self-organizing map (SOM) belongs to the artificial neural network (ANN) category, trained by unsupervised learning. SOM objective is to generate a low-dimensional - typically two-dimensional - discretized representation called a map, offering a dimensionality reduction method in the input space of training samples (Z. Zhou et al., 2020; Zhang et al., 2020). In this context, SOM offers a significant advantage, as it improves data interpretability. By clustering in grids and reducing dimensionality, data become more accessible, facilitating the identification of underlying patterns (Fan et al., 2021). In this paper, MODWPT was used as the signal processing method for decomposition. Afterwards, PCA was applied to reduce the dimensions while preserving the stable signal features. A comparison with EMD-PCA is presented to assess the advantages of the proposed approach. The final step in the proposed methodology incorporates the use of the self-organizing map (SOM) for defect clustering. SOM, a neural network-based algorithm, categorizes faults on the basis of extracted features, providing a sophisticated clustering process. This enhances defect detection and analysis by offering a nuanced exploration of relationships and patterns in vibration data.

2. Proposed Methodology

This section aims to present the different steps of the proposed methodology. First, raw data are injected to the Maximal Overlap Discret Wavelet Packet Transform (MODWPT) to extract features by filtering the signal and enhance their dimensionality. Then, the obtained new data passes through Principal Component Analysis (PCA) for reducing dimensionality by converting intricate vibration signals into a collection of uncorrelated principal components. After that, a 3D representation of the three principal components (PCs) of different health state under variable working conditions will be generated. Finally, a self-organizing map (SOM) is used to classify the different patterns for faults diagnosis. And overall view of the proposed technique is presented in Figure 1.

3. Maximal Overlap Discret Wavelet Packet Transform

The raw data is initially segmented into 25 groups, each consisting a length of 10024 samples. This segmentation is carried out as a preliminary step for data augmentation, a process aimed at enhancing the dataset's diversity and robustness by generating additional instances. The MODWPT uses segmented raw data as input for multi-stage filtering, resulting in a greater number of vibration time-frequency bands.Similar to Mallat's algorithm (Afia et al., 2024a), MODWPT relies on quadrature mirror filters. The filters, denoted as and, represent a low-pass and a high-pass filter, each with a length of L=10024 samples (assumed to be even). For this purpose, 16 resulting wavelet coefficients (decomposed signals) are obtained from MODWPT filters, as presented in Equation 1.

$$\left\{ \begin{array}{l} \displaystyle\sum_{l=0}^{L-1} \tilde{h}_l^2 = \frac{1}{2} \\ \displaystyle\sum_{l=0}^{L-1-2k} \tilde{h}_l \tilde{h}_{l+2k} = 0, \quad k = 1, 2, ..., \frac{1}{2}(L-2) \\ \tilde{g}_l = (-1)^{l+1} \tilde{h}_{L-l-1}, \quad l = 0, 1, ..., L-1 \end{array} \right\} \tag{1}$$

MODWPT diverges from Mallat's method by employing interpolation two-based decimation operation. More precisely, at each MODWPT level, $(2^{j-1} - 1)$ zeros are introduced between two consecutive adjacent coefficients of $\widetilde{g}_l$ and $\widetilde{h}_l$. This ensures that the wavelet coefficients generated (WT) for each wavelet sub-band maintain an equivalent length to that

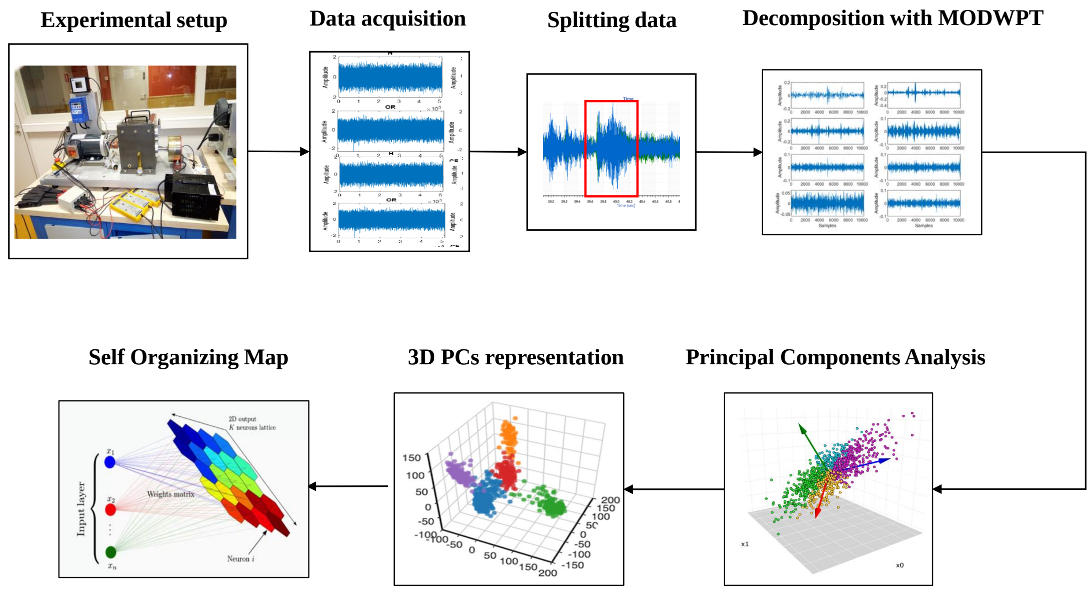

Figure 1. Overall view of the proposed technique.

of the input signal (Afia et al., 2024a). Considering a discrete-time sequence $x(t), t = 0, 1, \ldots\ldots, N-1$, where N represents the sequence length, the wavelet coefficients $W_{j,n,t}$ of the nth sub-band at level j are computed using the following equations, with n taking values from $0to2^j - 1$. The initial condition is given by $W_{0,0,t} = x(t)$ [14]. For a discrete-time sequence$x(t), t = 0, 1, \ldots\ldots, N-1$, where N is the sequence length, the wavelet coefficients$W_{j,n,t}$ of the nth sub-band at level j are calculated according to the following equations in which $n = 0, 1, ..., 2^j - 1, W_{0,0}, t = x(t),\ t = 0, 1, ..., N-1$ (Afia et al., 2024a):

$$W_{j,n,t} = \sum_{l=0}^{L-1} \tilde{f}_{n,l} \, W_{j-1,[n/2](t-2^{j-1}l) \bmod N} \tag{2}$$

$$\tilde{f}_{n,l} = \begin{cases} \tilde{g}_l, & \text{if } n \bmod 4 = 0 \text{ or } 3 \\ \tilde{h}_l, & \text{if } n \bmod 4 = 1 \text{ or } 2 \end{cases} \tag{3}$$

4. Principal Components Analysis

This step of the methodology aims to exploit the wavelets coefficients data for anomaly detection. For this purpose, the obtained data matrix, comprising 16 wavelet coefficients with 10024 samples(16,10024), is fed into PCA for dimensionality reduction and 3D visualization. In fact, conventional literature works aims to use extracted features and directly train Machine Learning (ML) models for classification. This procedure lacks efficiency with regard to train a ML model, already considered as a black box, with no verified and reliable feature. In such a scenario, PCA generates stable Principal Components from various vibration health state signals. PCA is proving advantageous in vibration signal analysis for fault diagnosis due to its multiple benefits (Shi et al., 2020). PCA excels in dimensionality reduction, transforming complex vibration signals into a set of uncorrelated principal components. This simplifies subsequent analysis, improves computational efficiency and provides a concise representation of essential information. PCA contributes to noise reduction in vibration signals. By emphasizing the principal components associated with the greatest variances, PCA actually mitigates the noise impact, making it particularly useful in environments where the signal-to-noise ratio is a significant concern. PCA can be conceptualized as an unsupervised learning problem. The process of deriving principal components from a raw dataset can be simplified into six steps:

1. **B**egin with the entire dataset, initially comprising d+1 dimensions, and disregard the labels, resulting in a new dataset of d dimensions.
2. **C**alculate the mean for each dimension across the entire dataset.
3. **C**ompute the covariance matrix for the complete dataset; where i is the samples number of signal X. are the mean of X,Y signals.

$$Cov(X,Y) = \frac{\sum_{i=1}^{n} \left(X_i - \overline{X}\right)\left(Y_i - \overline{Y}\right)}{n-1} \tag{4}$$

4. **D**etermine the eigenvectors and their corresponding eigenvalues.

$$Cov(X,Y) \times \sum\nolimits_{Value} = \sum\nolimits_{Value} \times \sum\nolimits_{Vector} \tag{5}$$

5. **A**rrange the eigenvectors in descending order based on eigenvalues, selecting k eigenvectors with the highest

eigenvalues to create a d×k dimensional matrix, denoted as W.

6. Utilize this d × k eigenvector matrix (W) to transform the samples to obtain the new set of uncorrelated variables.

5. Self Organizing Map

A Self-Organizing Map (SOM) is an unsupervised machine learning algorithm used for clustering and visualization of high-dimensional data. SOM is employed to identify patterns and anomalies in complex systems. SOMs consist of a grid of nodes (neurons) organized in two dimensions [29]. Each neuron is associated with a weight vector that is adjusted during the learning process. The best matching unit (BMU) weights and its neighboring neurons are adjusted to move closer to the input pattern. Neighboring neurons in the SOM grid respond similarly to similar input patterns, forming clusters (Figure 2).

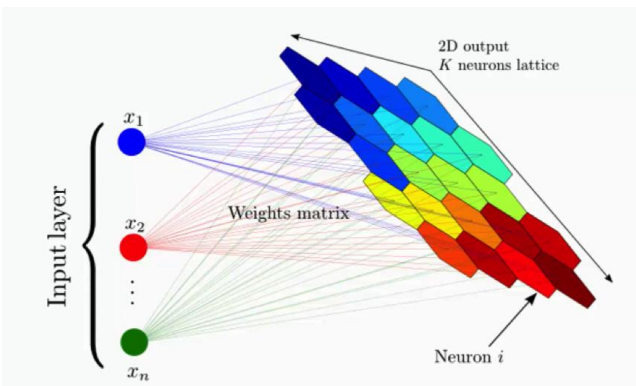

Figure 2. Self-organizing map architecture.

6. Application and results

The described methodology is applied to experimental data, which includes various fault states as well as a healthy state. The experimental setup is designed for multi- faults classification. With the proposed methodology, our objective is to evaluate the effectiveness of the extracted features in separating the different health states.

6.1. Case Study

To verify the applicability of the proposed methodology, an open access data of test bench provided and presented in (M. Soualhi et al., 2023). The test bench chosen in this study is Laboratoire d'Analyse des Signaux et Processus Industriels (LASPI) benchmark that introduce bearing and gear fault detection and diagnostic problem(Figure 3). It consists of a three-phase inverter controlling a 1.5 kW induction motor driving the gearbox. An electromagnetic brake connected to the gearbox simulates the motor load.

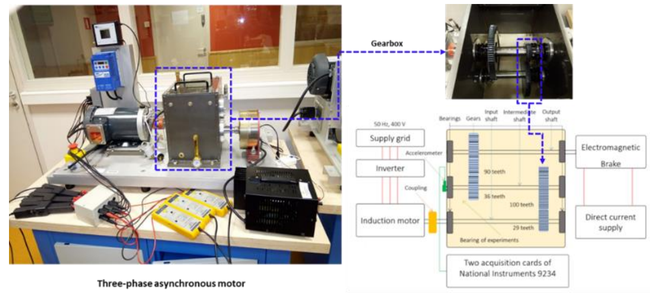

Figure 3. LASPI Benchmark.

The gearbox consists of three shafts: input, intermediate and output, with the studied bearings located on the intermediate shaft. The input shaft, connected directly to the motor, features a 29-tooth gear and two bearings with 9 balls each. The bearings have a 0.3125" diameter, a 1.5157" pitch diameter and a 0" contact angle.

Measurements are conducted in continuous mode for 10 seconds, with a 25.6 kHz sampling frequency. Vibration signals are acquired with an accelerometer sensor with a 100 mV/g sensitivity. Using the specified test rig instrumentation, a total of five distinct health states were examined, encompassing healthy bearings, inner, outer ring defects and combined bearing defects. In addition, each condition was tested at two different speeds: 25 Hz. Furthermore, each speed condition was tested at two load levels: 0%, 50% and 75%.

6.2. Result and discussion

The used raw data represent different states of bearing and gears. Each signal is first splitted into 25 segments. Figure 4 displays the different acquired vibration signals. Subsequent

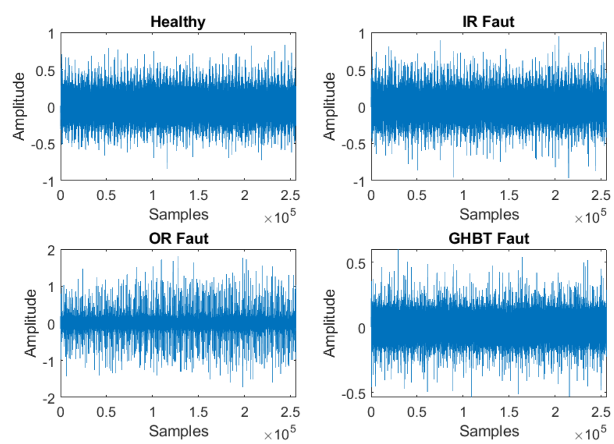

Figure 4. Vibration signals of different health states.

steps involve applying MODWPT to the segments in order to decompose each signal into its different frequency components, thus obtaining a detailed signal representation in the time and frequency domains(Figure 5).

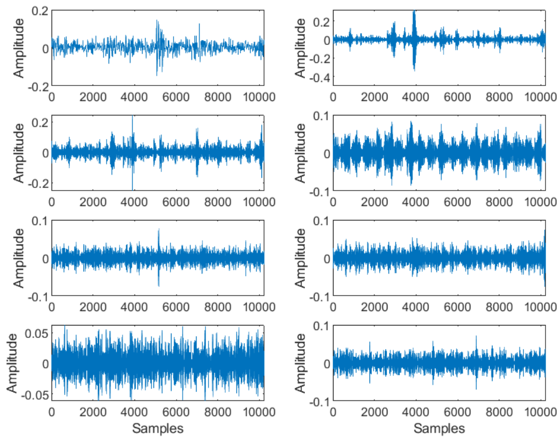

Figure 5. MODWPT decomposition.

PCA is applied to the decomposed modes, enabling a more concise data display by focusing on the dominant features. This step is crucial for simplifying the data set while retaining the essential information, thus facilitating analysis and interpretation.

Figure 6 illustrates the sample distribution under variable working conditions $(0\%, 50\% and 75\% load)$ using EMD-PCA. In the visual representation depicted in Figure 6, a noticeable level of sample confusion is obvious. This intricacy involves complex patterns and overlapping samples in the dataset, leading to a significant degree of imprecision in the extraction process. Recognizing the critical nature of this issue, our proposed solution is a hybrid MODWPT-PCA technique.

Figure 7 provides a more accurate sample distribution between the different health states. In comparison with the EMD-PCA, the advantages of the proposed approach in the feature extraction step are affirmed, demonstrating the proposed methodology's effectiveness. For automated fault diagnosis, a self-organizing map (SOM) is used to cluster neighboring neurons that respond similarly to analogous input patterns. The extracted data from MODWPT-PCA which containing 100 samples (25 samples for each 4 health states) and three columns (3 Principal Components) is used as input data for SOM model. Figure8 shows the sample clustering map using the proposed methodology for the four health states under three distinct working conditions.

After examining the map clustering (Figure 8), a significant sample separation is seen across distinct health states under different working conditions. This validates the reliability of the suggested diagnostic methodology.

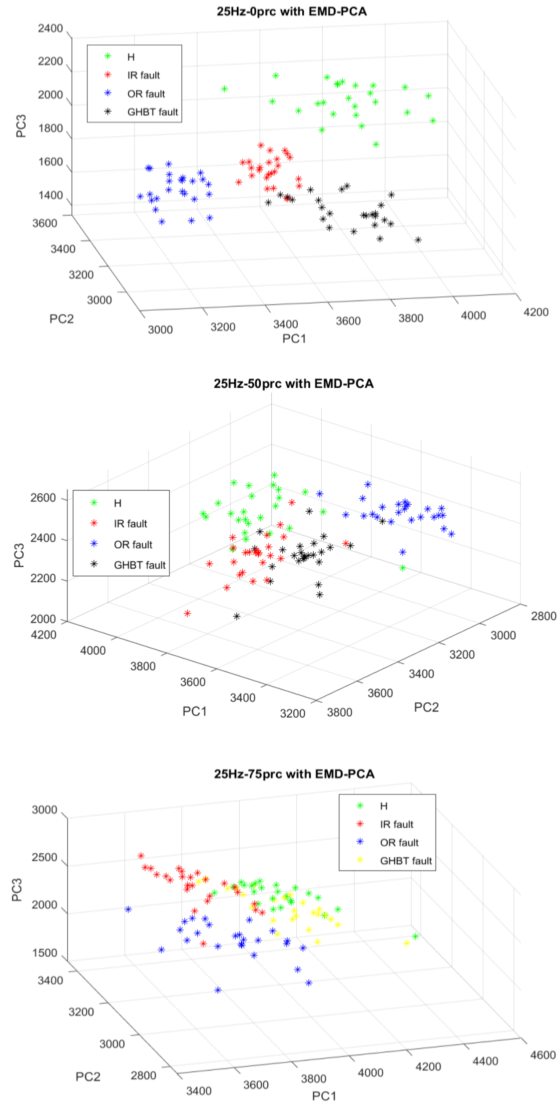

Figure 6. Samples distribution using EMD-PCA.

7. Conclusion

In this paper, the authors proposed a hybrid technique to address the inherent limitations of hidden fault characteristics in fault diagnosis. The approach integrates Maximal Overlap Discrete Wavelet Packet Transform (MODWPT) and Principal Component Analysis (PCA). MODWPT efficiently decomposes data signals with uniform frequency bandwidth, while PCA proves advantageous for feature extraction in vibration signal analysis. PCA captures variance, enabling the identification of significant defect-related patterns. A comparison with EMD-PCA is then conducted to assess the performance of the suggested algorithm. Finally, a self-organizing map (SOM) is used for machine learning to cluster the acquired data samples. The experimental results highlight that the proposed methodology is highly efficient in extract-

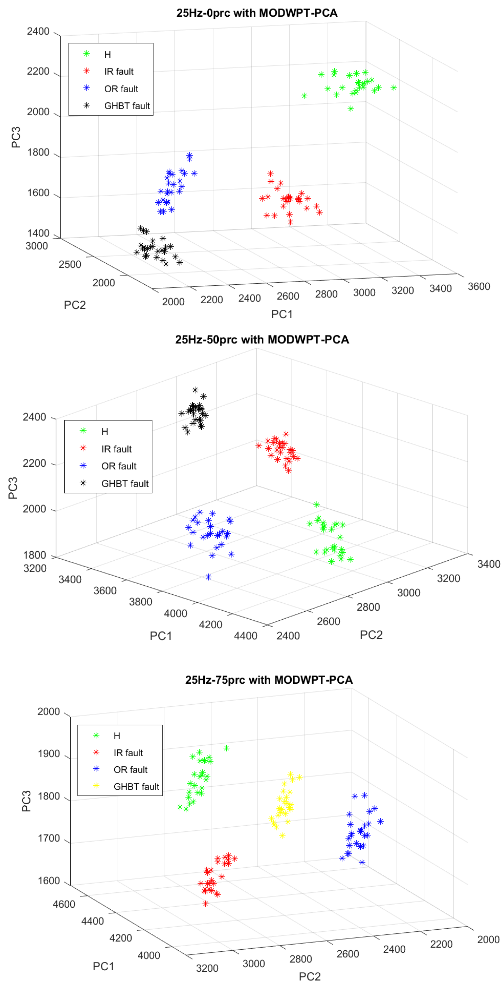

Figure 7. Samples distribution using MODWPT-PCA.

ing fault signatures from raw vibration data, even in a complex working environment.

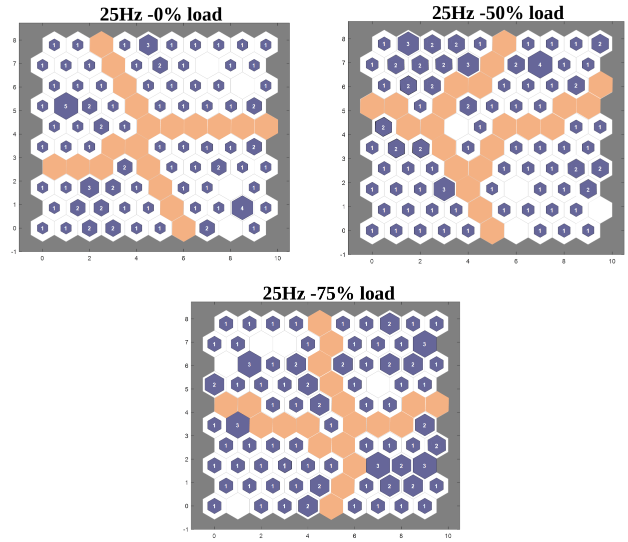

Figure 8. SOM clusters map.

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